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**By**

**Shin S. Ikeda**

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NATIONAL GRADUATE INSTITUTE  
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National Graduate Institute for Policy Studies  
7-22-1 Roppongi, Minato-ku,  
Tokyo, Japan 106-8677

# An Empirical Market Microstructure Analysis of the Implied Spread Cost in the Japanese Day-Ahead Electricity Market

Shin S. Ikeda\*

National Graduate Institute for Policy Studies

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## Abstract

Historical data of system prices over 48 half-hour intra-daily intervals in the Japan Electric Power Exchange (JEPX) are analyzed. Given theoretical and graphical preliminary analysis, we extract measures of the spread between the efficient price and actual transaction price for each month from November 2006 to April 2012. The measures are based on the first-order serial covariance of transaction returns proposed by Roll (1984) and on the historical highs and lows with some bias correction proposed by Corwin and Schultz (2012). Viewed as measures of the marginal costs of trading in the JEPX, the estimated spreads are on average at least 50 times as large as the one in the well-functioning S&P500 index futures market. The traded amount of electricity does not explain the variation of spreads once the time-of-a-day fixed effects and month-specific time effect are explicitly accounted for in the panel regression.

**Keywords:** Market Microstructure, Implied Spread, Roll measure, Periodic Call-Auction, Wholesale Electricity Market.

**JEL Classification Numbers:** G14, Q41.

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# 1 Introduction

The Japanese Electric Power Exchange, or the JEPX henceforth, launched in April 2005. This exchange market was established for the purpose of increasing the liquidity and therefore flexibility of electricity trades among different players with the potential ability of power generation. In addition to the traditional regionally monopolistic general electricity suppliers (regional monopolists, henceforth), the market invited the other new entrants, the so-called Independent Power Producers (IPPs) having their own power generators and selling the electricity to the regional monopolists, and Power Producer and Suppliers (PPSs) having the their own power generators and selling the electricity to customers of large scales via the electricity transmission system owned by the regional monopolists.

However, the amount of electricity traded through the JEPX is only 0.6% of the total amount traded in the fiscal year of 2010<sup>1</sup>. The great earthquake on 11-March-2011 hitting the northeastern coast of Japan caused the breakdown of the Fukushima nuclear power plant operated by the TEPCO, one of those regional monopolists in Tokyo. Amid the confusion in the electricity supply/demand market, TEPCO stopped supplying electricity to the JEPX for a while. It triggered exits of several members from the exchange because of the shrinking benefit relative to the membership cost. This anecdotal evidence suggests that the JEPX does not flexibly function at all to adjust, even partially, the tightening demand-supply condition in the turmoil of electricity market. It raises the question on whether the JEPX trading mechanism is really well designed and whether it is efficient.

The efficiency of different trading mechanism in the financial market has been studied in the field of market microstructure. The key notion of the transaction cost in several financial markets with the so-called dealers, or market makers, is the positive discrepancy between the prices for selling and buying a security. This is called the bid-ask spread, and it has attracted great interests from the academics and professional traders in the financial industry. Although the bid-ask spread exists explicitly in the market driven by such dealers and not in the periodic single-price call-auction mechanism as is explained later, several studies have found similar types of empirical regularities even in such kind of exchanges without designated dealers. The JEPX falls within the realm of the latter category. Therefore, the analysis of implied spread as a measure of marginal cost associated with the trading in the JEPX has some meaning, but it requires a careful justification in terms of economic principles.

The data from the JEPX have been studied by several authors: to name a few, Ofuji and Yamaguchi (2008) and Kawamoto and Sakanashi (2010). However, those papers tend to adopt statistical or mechanical approaches. It may be the case that the sluggish progress of the activity in the JEPX is attributable to the failure of an appropriate economic design of the market. To see how (in)efficient this exchange has been, it is crucial to find some measures of (in)efficiency of the trading mechanism. The purpose of this paper is to give the first empirical documentation of the implied spread cost obtained from the transaction prices in the JEPX. By combining several theoretical predictions from the literature of market microstructure and simple statistical tools to infer the implied spread from the first order serial covariance of transaction returns, we can

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<sup>1</sup>[http://www.cao.go.jp/sasshin/kisei-seido/meeting/2011/energy/120112/item5-2\\_5.pdf](http://www.cao.go.jp/sasshin/kisei-seido/meeting/2011/energy/120112/item5-2_5.pdf)

show that the spread cost in the JEPX may be at least 50 times larger than the well-functioning S&P500 index futures market. This magnitude of marginal cost may partially account for the sluggish improvement of the trading condition in the JEPX.

Here is the subsequent structure of this paper. In Section 2, we review the characteristics of electricity as a commodity for trade in the open market, the institutional background of the JEPX and some strands of the market microstructure theory potentially relevant for the analysis of the JEPX. Section 3 deals with the introduction of the permanent-transitory model of observed transaction prices, and relate them to the implied spread cost structurally. They naturally induce two types of spread estimators. Section 4 gives the preliminary data analysis in the first half and the estimation of the spread in the second followed by some discussion about the magnitude of the estimated spread and plausible explanations from some market microstructure models. Section 5 concludes the paper.

## 2 The Implied Spread Cost in the JEPX

### 2.1 Some characteristics of electricity as a non-storable commodity

It is very hard to store electricity as a commodity. Therefore, the generated electricity should be consumed for a very short period of time. The excess demand for electricity causes the lower voltage, unstable frequency and, for the worst case, a black-out over a broad area. To avoid this devastating event, the Japanese regulatory board dictates the regional monopolistic electricity companies to instantaneously match the supply and demand of electricity. On the other hand, the other PPSs are allowed to match the demand and supply up to  $\pm 3\%$  deviations only within the half-hour interval. To encourage the entry of new PPSs and induce the increase of electricity supply in the market, the JEPX offers trades of electricity over 48 half-hour intervals within a day. The execution price and quantity of electricity in these 48 intervals in a specific day are determined simultaneously in the JEPX. Therefore, they should be viewed as 48 different commodities rather than a time-series of a single commodity. This last point is important for conducting the panel analysis of estimated spreads later in Section 4.4.

### 2.2 Institutional Aspects of the JEPX Market

The market-clearing mechanism in the JEPX market is the “Itayose” method. It is a version of the periodic single-price call-auction with a batch trading, i.e. the accumulated orders are executed simultaneously at a single price that matches the market demand and supply. Orders of buy (positive) and sell (negative) for the delivery of electricity in a specific day are submitted to the JEPX system between 10 AM to 4 PM from six to two business days before that day; and from 8:30 AM to 9:30 AM in the business day just prior to it. An order schedule is composed of several limit prices. For the demand (supply) side, a limit price is the maximum (minimum) price acceptable for buying (selling) a certain amount of electricity. The individual demand and supply schedules are not smooth curves but assemblies of semi-open vertical segments corresponding to several discrete amounts of electricity with kWh/h as the unit. They have jumps in the axis of quantities as shown in Figure 1. All schedules are aggregated into the market supply and demand schedules. Their intersection determines a single market-clearing

price for all feasible trades. All players in this market must pay the commission fee and deposit. The deposit takes care of the cost of non-fulfillment of the agreed demand or supply of electricity. For a buyer, it limits the total amount of payment allowed in bidding the demand schedule. For a seller, it covers the potential compensation to a buyer if it cannot deliver the whole amount of electricity owing to, e.g., the breakdown of a power generator. The deposits for all trades in one month are reserved until the next month, then paid back to each player after subtracting these compensations. Therefore, a foregone interest incurs an opportunity cost of transaction. It should also be noted that the power transmission line system is owned by the regional monopolists. Therefore, whenever a PPS is supposed to deliver electricity, it incurs some cost to be paid to the regional monopolists. Finally, because of the multiple suppliers and demanders involved in the agreed amount of electricity to be traded, the negotiation in case of non-fulfillment of the contract can be messier than the bilateral contract with a regional monopolist.

Because the entire schedules are given by assemblies of individual orders, JEPX falls within the realm of an order-driven market. On the other hand, a large part of the market microstructure analysis in the financial sector is focused on the quote-driven mechanism. In this mechanism, mutually competing dealers or market makers publicly post their ask quotes and bid quotes (candidates for seller's and buyer's prices, respectively). All customers can observe all posted quotes and decide to buy or sell desired amounts of securities at a more advantageous quote. Each dealer can determine the size of a bid-ask spread (ask minus bid). The competition among dealers is expected to squeeze, but not eliminate, this spread because the dealership incurs some marginal cost and because the dealers collectively behave as a monopolist to maximize their collective profit. The marginal cost for market participants, realized as the bid-ask spread, involves three different components stemming from different economic principles. (i) The order-processing cost such as the clearing fees and per trade allocations of fixed costs for, e.g., computers, telephones, high-speed servers, and so on. The observed price can fluctuate without any surprising news regarding the intrinsic value of a security. It is typically observed as the price-reversal, known as the bid-ask bounce. Therefore, dealers as a collective monopolist have incentive to cover this marginal cost of transaction by keeping the bid-ask spread. Then, the efficient equilibrium price should be somewhere in the middle of quoted ask and bid. The earliest contributions along with this argument are Demsetz (1968), Tinic (1972) and Roll (1984). (ii) The inventory cost in preparation for random arrival of large order imbalance. Garman (1976) establishes a model for the bid-ask spread as an instrument for dealers to control the intensity of a Poisson-type random arrival of orders. A wider spread discourages the intensity of order arrival and is expected to keep the inventory of dealers solvent. Dealers want to set this spread so as to maximize the expected profit, again as a monopolist collectively. (iii) The cost of adverse selection. Some traders may have more information than the others regarding the intrinsic value of a security. However, the dealers cannot make a distinction between these two types of traders. Only they can use is the order direction: the buy orders should come from customers with a private positive opinion of a security's intrinsic value and not from customers with a private negative opinion. Collectively as a monopolist, the dealers set the ask and bid quotes by maximizing the expected revenue from uninformed traders accepting an invalid level of price relative to the intrinsic value minus the expected cost incurred by the informed traders

exploiting their informational superiority. The resulting spread is wider if the set of traders is more asymmetric in their information. This is a basic mechanism of Copeland and Galai (1983) and Glosten and Milgrom (1985).

## 2.3 Motivation for Measuring Implicit Spreads, Immediacy and Inelasticity

As is noted previously, the trading mechanism in the JEPX is an order-driven, periodic single-price call auction with a batch trading. Therefore, all economic models as above regarding the trades of customers with collectively monopolistic dealers may not be appropriate. In particular, there are no such things as the bid and ask quotes: the executed price is always selected as a single price equating the market demand and supply and prevails for all feasible quantity of electricity to be traded. However, Roll (1984) emphasizes that his example of a trade with dealers is just for an illustrative purpose. Regarding “ $s$ ” as the constant bid-ask half spread, he notes that<sup>2</sup>

*...  $s$  is not necessarily the quoted spread. Successive price changes are recorded from actual transactions ...  $s$  is the effective spread, i.e., the spread faced by the dollar-weighted average investor who actually trades at the observed prices...  $s$  is the average absolute value of the price change when the price does change and yet no information has arrived. (Roll 1984, p.1129-1130).*

Amihud and Mendelson (1991) study the efficiency of different trading mechanism based on tick-data of security returns from the Tokyo Stock Exchange (TSE). TSE has morning and afternoon sessions divided by the lunch-time break. The opening prices of both sessions are determined by the Itayose method. They find significantly negative first order autocorrelation of the open-to-open returns (e.g., the return from the opening price in a morning session to the opening price in the next morning session). They owe this puzzling existence of serial correlation of returns from the Itayose mechanism to the inefficiency of the TSE in the sense of Fama (1970) and to the illiquidity effect of Roll (1984). Because there are no well-defined publicly quoted spreads for the opening prices in TSE, they essentially adopt Roll’s view as above. Haller and Stoll (1989) find a pattern of serial covariance of returns of securities traded in the call-auction German stock market as is similar with the one observed in the dealer markets. Madhavan (1992) gives a similar argument as the previous view by Roll:

*... even in an auction system with one price, an analogous measure or effective bid-ask spread can be constructed because buy orders raise prices while sell orders lower prices. (Madhavan 1992, p.615).*

This remark basically means that the auction system adopted in several financial markets do allow for some players to have market power. Stoll and Whaley (1990) introduce the notion of an implied spread regarding the price reversal phenomena:

*Price reversals reflect the compensation of suppliers of immediacy for taking the other side of transactions initiated by active traders... In an auction market, similar*

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<sup>2</sup>The effective spread in this quote means a spread measure implied from the serial covariance of transaction returns. Recently, the “effective spread” is usually defined as the discrepancy between the actual transaction price and the mid-quote, i.e. exactly the middle point between the best ask and the best bid quotes.

*reversals are observed even though no bid-ask spread is quoted because suppliers of immediacy back away from active traders. (Stoll and Whaley 1990, p.54-55.)*

Hasbrouck (2007, Section 11.5) suggests that a classical inventory model of dealers by Garman (1976) may be useful given an appropriate re-interpretation:

*Garman's view of dealers as smoothers of buy/sell order imbalances continues to be useful... the perspective also applies when temporary order imbalances arise in the aggregate. Dealers are agents who ... accommodate these imbalances... At the same time, the lines between dealers and customers in many markets have blurred... if inventory control is more broadly interpreted as position management, the issues are as pertinent as ever. (Hasbrouck 2007, p.116-117.)*

In addition to these economic stories, let us finally add some technical but important real-world condition, the price discreteness. Because the JEPX is order-driven, and because the aggregate orders are assemblies of limit order schedules, the market demand and supply functions may still look like a step function rather than a smooth curve if the number of players is limited and some of them have a large market power than the rest. Figure 1 illustrates how the execution price and quantity are determined in the market. The red and blue segments represent the aggregated market demand schedule and supply schedule, respectively. The execution price and quantity are given by

$$P^* = \inf\{P \geq 0 : D(P) \geq S(P)\}, \quad Q^* = \min\{D(P^*), S(P^*)\}.$$

The definition of  $P^*$  involves the infimum and not the minimum. Figure 1 explains why this is the case: the demand and supply schedules are touched upon with each other in their vertical parts. Notice that the line segment for the demand includes the upper end point but not the lower end point, as the reflection that a buyer's limit price is the worst, namely the maximum, acceptable price for a certain amount of electricity delivery, whereas the line segment for the supply shows the opposite pattern reflecting nature of a seller's limit price. In this case, there is no minimum achieving the above relation because the lower end point is not included in the demand schedule. The indicated equilibrium price will induce the potential demand  $D(P^*)$ . On the other hand, the supply schedule does include the lower end point so that it induces the potential supply  $S(P^*)$ . Because  $S(P^*) < D(P^*)$  in this case, only  $Q^* = S(P^*)$  is feasible for transaction.  $P^*$  cannot be the minimum price such that  $D(P) \geq S(P)$  holds.

If the supply decreases slightly or demand increases slightly while the counterpart is fixed as a deviation from Figure 1, it may cause a sharp price increase as Figure 2 shows. The transition from Figure 2 to Figure 1 induces the opposite case, i.e., a sharp decline of the equilibrium price. Note that the change of equilibrium price in that case is a conservative measure of the length of this vertical segment of the supply schedule at the old equilibrium quantity. We can think of this measure as the local inelasticity of a market supply function. It also constitutes the implied bid-ask spread as discussed above. If the demand schedule is perfectly inelastic, as assumed in Kanamura and Ohashi (2007), the price change associated with such fluctuation of

the supply or demand perfectly reveals this inelasticity<sup>3</sup>.

The issue of a price discreteness is raised by an impressive regularity of daily returns plotted against its first-order lagged values by Crack and Ledoit (1996). The plot shows the so-called “compass-rose” pattern: it shows many straight rays emanating from the origin instead of crowdly scattered points. The cause of this pattern is the discreteness of price from rounding a continuous counterpart to the nearest grid determined by the minimum tick of price variations. Fang (2002) shows by simulations that some representative random-walk tests suffer from a severe size inflation if the rounded grid is in dollars rather than 1/8 dollars or cents. This means that spurious serial correlation may be detected given a rough rounding procedure. It should also be emphasized that Christie and Schultz (1994) raise the issue of the unit of minimum variations of observed prices and its relation to the size of bid-ask spread. The possible effect of discreteness appears as a part of the implicit spread around the efficient log price. Therefore, the measurement of implied spreads is important for checking if the JEPX market is well functioning in terms of the informational, institutional and regulatory efficiency.

### 3 Modelling Implied Spreads of 48 Half-Hour Electricity Prices

#### 3.1 Permanent-Transitory Model of Efficient Log Price and Spread

Here is the list of structural assumptions in this paper.

**Assumption 1** (*The data-generating mechanism*)

1.  $t \in [0, 1]$  defines an appropriate unit of interval in time.  $(\Omega, \mathcal{F}, \mathcal{P}, \mathbb{F})$  is the filtered probability space where the filtration  $\mathbb{F} = (\mathcal{F}_t)$  is left continuous and is augmented by the  $\mathcal{P}$ -null sets.  $\mathcal{F}_t = \mathcal{G}_t \vee \mathcal{H}_t$  is the minimum  $\sigma$ -field containing coarser sub- $\sigma$ -fields  $\mathcal{G}_t$  and  $\mathcal{H}_t$ .  $\mathbb{G} = (\mathcal{G}_t)_{t \in [0, 1]}$  is the Brownian filtration while  $\mathbb{H} = (\mathcal{H}_t)_{t \in [0, 1]}$  is the filtration generated by the market microstructure effect.
2. For  $t \in [0, 1]$ , the efficient log price of  $j$ -th electricity commodity,  $\ln P_j^*(t)$ , follows

$$d \ln P_j^*(t) = \sigma dW(t) \quad (1)$$

where  $W(t) \sim N(0, t)$  is the Brownian motion representing the market risk and  $\sigma$  is the constant standard deviation of instantaneous returns.

3. The actual transaction price of  $j$ -th commodity  $P_j(t_i)$  at  $i$ -th discrete observation time  $t_i = 1/n \in [0, 1]$  is subject to a percentage deviation from the efficient counterpart: for  $i = 0, 1, \dots, n$ ,

$$P_j(t_i) = P_j^*(t_i)(1 + S_j(t_i)/2) \quad (2)$$

where  $S_j(t_i)$  is independent and identically distributed round-trip spread associated with  $j$ -th commodity for any  $t_i \in [0, 1]$  and is independent of  $P_j^*(t_i)$ , and  $S_j(t_i) = +s_j$  with the

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<sup>3</sup>If the fluctuation of the supply or demand is relatively large, the change in the equilibrium price from the last one may correspond to the sum of lengths of multiple line segments.



unconditional probability  $p_j$  and  $S_j(t_i) = -s_j$  with the unconditional probability  $1 - p_j$ . Alternatively, by taking the natural logarithm in both sides of (2),

$$\ln P_j(t_i) = \ln P_j^*(t_i) + \ln(1 + S_j(t_i)/2) =: \ln P_j^*(t_i) + U_j(t_i). \quad (3)$$

There are several remarks on these structural assumptions.

First, the filtered probability space supports any randomness in this setup. The filtration  $\mathbb{F}$  summarizes the evolution of all relevant information.  $\mathbb{G}$  is the information filtration generated by the market risk of electricity price- it is a public information in the model. On the other hand,  $\mathbb{H}$  is the information associated with the implied spreads that can reflect the private information and therefore  $\mathbb{H}$  may be different from  $\mathbb{G}$ .

Second, the actual transaction prices in logarithm deviate from their efficient counterparts, as is indicated in (3). This modeling strategy tracks several models in the literature of market microstructure (see, e.g., Hasbrouck 2007) and the volatility estimation using noisy high frequency data (see, e.g., Bandi and Russell 2008). Note that given our percentage-deviation form in (2), the additively separable component  $U_j(t_i)$  in (3) is a concave transform of  $S_j(t_i)$ . This formulation is also adopted implicitly by Corwin and Schultz (2012).

$S_j(t_i)$  is the round-trip spread, namely, the spread cost for some participant in the market changing his/her role from a seller to a buyer. The half spread  $s_j/2$  is more directly attached with the marginal cost of order executions. The i.i.d. nature of  $S_j(t_i)$  and independence from  $P_j^*(t_i)$  are made for simplicity, and it leaves important aspect of the serial correlation in the implied half spread as well as the information content of the order direction as emphasized in the adverse selection model of Copeland and Galai (1983) and Glosten and Milgrom (1985). We adopt this restrictive assumption because our data contain only the history of execution prices and quantities and not directions of orders.  $p_j$  is not necessarily  $1/2$ , and it is assumed later to enforce  $E[U_j(t_i)] = 0$  rather than  $E[S_j(t_i)] = 0$ .

### 3.2 Estimators of the implied spread based on transaction prices

As will be explained in the next section, all we can use for the analysis of returns of electricity commodity in the JEPX market is the transaction (or executed) prices. Therefore, any estimators of the implied spread should be solely based on the transaction prices: we cannot use the ask or bid quotes, the direction of trades, etc. There are two relevant candidates.

The first and perhaps the easiest candidate is given by Roll (1984) based on the serial covariance of transaction returns. The idea is simple: if the efficient log price follows a random-walk type model, as is indicated in (1) above, then the return series  $\Delta \ln P_j(t_i) := \ln P_j(t_i) - \ln P_j(t_{i-1})$  does not have serial correlation. If we have additively-separable i.i.d. spread factor,  $\ln P_j(t_i) = \ln P_j^*(t_i) + U_j(t_i)$ , however, the first-order serial covariance is given by

$$E[\Delta \ln P_j(t_i) \Delta \ln P_j(t_{i-1})] = -E[U_{t_i}^2]$$

because  $S_j(t_i)$  and therefore  $U_j(t_i)$  is i.i.d., independent of  $\ln P_j^*(t_i)$  and  $\Delta \ln P_j^*(t_i)$  is the efficient return, which is serially independent. Supposing  $p$  dictates  $E[U_{t_i}] = 0$ , as is common in the literature of volatility estimation from the noisy high frequency data, and applying the

approximation  $\ln(1 \pm s_j/2) \approx \pm s_j/2$ ,  $Cov(\Delta \ln P_j(t_i), \Delta \ln P_j(t_{i-1})) = -var(U_j(t_{i-1})) \approx -s_j^2/4$  or  $\hat{s}_{j,Roll}/2 = \{-\widehat{Cov}(\Delta \ln P_j(t_i), \Delta \ln P_j(t_{i-1}))\}^{1/2}$ . If we have a negative estimate of the spread, we will always truncate it at zero. The Roll's spread measure has been scrutinized quite often. The general consensus in the literature is that it underestimates the implied spread. Based on Harris (1990) regarding this point, Shultz (2000) employs the following finite-sample correction:

$$\hat{s}_{j,Roll}^*/2 = \frac{\{-\widehat{Cov}(\Delta \ln P_j(t_i), \Delta \ln P_j(t_{i-1}))\}^{1/2}}{1 - 7/\{8(n-1)\}}. \quad (4)$$

This finite-sample correction factor, however, does not cause much difference as long as the daily data are used for estimating the monthly spread because  $1/[1 - 7/\{8(n-1)\}] = 1.03$  for  $n = 31$ . Jagadeesh and Titman (1995) also reaches the same conclusion that the Roll measure gives a conservative estimate of the implied spread. They also remark that the Roll's method may induce the over-estimation of spread based on, e.g., weekly observations. Therefore, it is informative to calculate the spread using the daily and weekly returns to bound the true spread.

The second candidate is recently proposed by Corwin and Schultz (2012), which is based on the maximum and minimum, or high and low, of transaction prices over a certain fixed period of time. Suppose we have two adjacent periods of time with the same continuous-time length, say  $A$  and  $B$ , and suppose we have data of highs and lows in these two periods separately and jointly. Supposing that the high and low prices should be associated with the positive and negative spreads, respectively, Corwin and Schultz (2012) derive the formula for  $s$ :

$$\begin{aligned} \hat{\beta}_j &= \left\{ \ln \left( \frac{\max_{t_i \in A} \{\ln P_j(t_i)\}}{\min_{t_i \in A} \{\ln P_j(t_i)\}} \right) \right\}^2 + \left\{ \ln \left( \frac{\max_{t_i \in B} \{\ln P_j(t_i)\}}{\min_{t_i \in B} \{\ln P_j(t_i)\}} \right) \right\}^2, \\ \hat{\gamma}_j &= \left\{ \ln \left( \frac{\max_{t_i \in A \cup B} \{\ln P_j(t_i)\}}{\min_{t_i \in A \cup B} \{\ln P_j(t_i)\}} \right) \right\}^2, \\ \hat{s}_{j,CS}/2 &= (e^{2.4142(\beta_j^{1/2} - \gamma_j^{1/2})} - 1)/(e^{2.4142(\beta_j^{1/2} - \gamma_j^{1/2})} + 1). \end{aligned} \quad (5)$$

See Corwin and Schultz (2012, Equation (18)) for (5). All we need to compute are  $\hat{\beta}_j$  and  $\hat{\gamma}_j$  for each  $j$ -th intra-daily half-hour interval using data over two adjacent intervals  $A$  and  $B$  with the same time length in  $[0, 1]$ . If the spread is small, we can obtain more direct approximation  $\hat{s}_{j,CS}/2 \approx 2.4142(\beta_j^{1/2} - \gamma_j^{1/2})$ . This expression suggests an interpretation of the Corwin-Schultz estimator as a range-based estimator of the spread with a jackknife-type bias correction.

Corwin and Schultz (2012) use the historical daily highs and lows. In this case,  $A$  and  $B$  correspond to two nearby trading days with the intra-daily observations for computing the daily highs and lows and two-day high and low. If we only have daily transaction prices without high/low information, we will content ourselves to use daily data to calculate highs/lows in a lower frequency, e.g. the 10-day interval for each of  $A$  and  $B$  or the 20-day period for the estimation, and let this window roll day by day to obtain about 10 estimates for a month. The monthly spread is then given by the average of these estimates. Whenever the spread estimate is negative, I also apply the truncation at zero.

## 4 Empirical Analysis of JEPX Transaction Prices

### 4.1 Characteristics of Data

There are two electricity networks in Japan, roughly corresponding to the east-west geographical division. The most stark difference in terms of electricity between the eastern and western parts of Japan is the frequency: it is 50Hz in the eastern part of Japan including Tokyo, while 60Hz in the western part of Japan including Osaka. This subdivision dates back to the earliest stage of regional monopolistic electricity companies who separately imported power generators either from Germany (in the east) or from the U.S. (in the west). As an integrated measure of the electricity price, the JEPX calculates and reveals the system price. It is a benchmark price when the east-west transmission of electricity happens to halt for any reasons. Our original data consist of all system prices and traded amount of electricity. In the earliest stage of the JEPX, the transactions were very small in volume and infrequent, sometimes without any posting of demand or supply. The last day of zero-posting in our original sample is 16-October-2006. Therefore, we select the sample period from 17-October-2006 to 30-April-2012, leaving 2027 days for each of the 48 electricity commodities, for the subsequent analysis. JEPX provide 48 commodities for 9 different locations in Japan, associated with 9 different regional monopolistic electric companies. Although it is possible to have 9 different price patterns for these areas, prices in Hokkaido and Tohoku are the same as the one in Tokyo (the eastern part of Japan), while the prices in Chubu, Hokuriku, Chugoku, Shikoku and Kyushu are the same as the one in Kansai (area including Osaka). Essentially, we only have two areas: east and west.

### 4.2 Graphical analysis of prices, traded quantities and returns

Figure 2 depicts the time-series average of system prices and traded quantities over the entire sample period in each half-hour interval. They show a clear time-of-a-day effect. The system price increases toward the noon, but there is a clear trough from 12 to 13 for the lunch-time break. The plot of the average traded quantities identifies 8 to 22 as the daytime period and the rest as the night-time period. Based on this figure, I pick 0-0:30 and 11:30-12 as two representative intra-daily intervals with the least and greatest activity.

Figure 3 collects the time-series plots of the system prices, traded quantities and the continuously compounded returns (the first differences of log prices) over the entire sample period for these two representative intra-daily intervals. The fluctuations of trajectories are visible for different periods of time within a day. The traded quantities in 11:30-12 show a pattern of the level-shift in the later period, corresponding to the aftermath of the great earthquake on 11-March-2011.

Figure 4 is a collection of quarterly-wise scatterplots of the system prices against the traded quantities. In early stages, the quantity-price pairs show very steep patterns. A trend may change from the fourth quarter in 2008, the rightmost panel in the first row. From then on until the fourth quarter in 2010 with the exception of historically hot summer in 2010, the quantity-price patterns are flatter and lower than those in the earlier period. This may be caused by entry of new PPSs, especially the gas companies, and their augmentation of power generation capacity. The patterns become steeper with higher prices on average again after

the great earthquake on 11-March-2011. Another interesting pattern in this figure is that the execution prices are almost always above 5 yen/kWh level. This may reflect the all-time backup system in which the regional monopolists are supposed to back-up the supply of PPSs to their customers if they are short of sufficient electricity. Although the price for this backup system is not publicly disclosed, these figures clearly show that any players have no incentive to sell electricity at prices below this lower threshold<sup>4</sup>.

Figure 5 summarizes the autocorrelation functions of daily returns for 8 different intra-daily half-hour intervals. The parallel breaking horizontal lines are boundaries of 95% confidence intervals for the white-noise null. The blue ones are for daily raw returns while the red ones are for daily non-zero returns. The degree of serial correlation seems milder for the non-zero returns than for the raw returns. In all half-hour intervals, the first order autocorrelation is significantly negative. Reflecting the day-of-a-week effect, the autocorrelation functions show 7-days cycle. Figure 6 stores autocorrelation functions for the weekly returns in 7 different days of a week. The different magnitudes of the first-order negative autocorrelation is visible for different days of the week are visible, especially for the interval from 11:30 to 12.

Figure 7 collects the compass-rose diagrams, namely, the plots of daily returns against their own first-order lags. For the less-active midnight interval, we can see some patterns of rays to the direction of horizontal and vertical axis, and from the north-west to south-east direction. The former correspond to the effect of zero-returns, whereas the latter seems indicating the first order serial correlation. Other than these, the pattern of rays is not so visible, especially in 11:30-12 interval, in contrast to those found in Crack and Ledoit (1996) and Fang (2002). It seems that the effect of discreteness of price in the JEPX may not matter so much for the empirically observed serial correlation. The weekly returns show virtually no such patterns.

The graphical data analysis so far suggests that the first order serial correlation in returns are real phenomena, and they may not be caused by the discreteness of price ticks. According to the previous section, some of market microstructure theory are applicable to the JEPX market as well- the inventory motives of immediacy suppliers and the transaction cost.

### 4.3 Measuring Implied Spreads

Figure 8 collects the estimated half spreads in each of 65 months from November 2006 to March 2012 using daily returns as inputs to the bias-corrected Roll estimator in (4). The left panel is the time series plots of half spreads in 48 half-hour intervals with the bold black and green trajectories as their cross-sectional mean and median. The median is computed as another measure of the central tendency of the estimated spreads with more robustness to outliers, as shown in the figure. However, they behave very similarly. We can see two spikes associated with the record-breaking hot summer in 2010 and the aftermath of 11-March-2011 great earthquake. The right panel assembles the cross-sectional patterns of half spreads for 48 different commodities in each month with the bold black and green as the time series mean and

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<sup>4</sup>A document (page 61) in Ministry of Economy, Trade and Industry summarizes prices for the backup. [http://www.meti.go.jp/committee/sougouenergy/sougou/denryoku\\_system\\_kaikaku/pdf/003\\_s01\\_01b.pdf](http://www.meti.go.jp/committee/sougouenergy/sougou/denryoku_system_kaikaku/pdf/003_s01_01b.pdf)  
Roughly speaking, they are floating between 6 to 10 yen/kWh so that 5 yen/kWh is indeed a lower bound.

median of the estimated spreads. Those numbers are percentages of the efficient prices<sup>5</sup>.

Figure 9 summarizes the estimated half spreads based on weekly returns. The day-of-the-week effect of spreads is evident. Weekdays contribute a lot to the average weekly spreads as indicated by the black breaking trajectory in each panel. The low and relatively flat spread estimates in Saturday and Sunday seem intuitive.

To see if the magnitudes of estimated half spreads are not dominated by the bias component associated with the specific combination of the Roll measure using daily returns, we also calculate the Corwin-Schultz estimator and the spread based on the Roll measure using the weekly returns. Figure 10 summarizes the time-series averages of three spread measures over the entire sample period. Three trajectories of half-spread estimates are largely in accordance with each other for the day-time period. Jagadeesh and Titman (1995) suggest that the Roll measure tends to under-estimate the true spread based on the daily returns and to over-estimate based on the weekly returns. In conjunction with the bias-corrected nature of Corwin-Schultz estimator and the associated trajectory roughly passing between these Roll-based trajectories in the active day-time intervals, our rough guess is that the true spread pattern is between blue real and blue breaking trajectories.

How large these estimated spreads are? Given the intra-daily interval 11:30-12, the time-series averages of the half spreads based on the Roll measure using the daily and weekly returns, and based on the Corwin-Schultz measure are 8.42%, 12.3% and 11.6% of the efficient prices, respectively. On the other hand, the time-series average of Roll spread measures based on returns from the closing prices of the S&P500 index futures is just 0.158%. Roughly speaking, the estimated half spreads, or the marginal cost of trading in the JEPX market, are at least 50 times as large as the one in the S&P500 futures market.

#### 4.4 Discussion and Connection to Market Microstructure

Based on the argument in Section 2.3, the estimated half spreads are potentially the mixtures of the following factors: (i) the transaction cost, (ii) the inventory cost, (iii) the adverse-selection cost, and (iv) the discreteness of price ticks.

For (iii) to be a valid hypothesis, it is necessary that the intrinsic value of a commodity is uncertain and therefore perceived differently by different participants in the market. In our case, however, the ultimate value of a traded security is electricity. It may be possible that some companies may have accessed to rich information about the government regulation or political risk to be reflected in the elevation of crude oil or liquid gas prices, they should not be enduring. Moreover, theoretical implication of the adverse selection model even in a dealer market is that the ask and bid quotes are given by the conditional expectations. Because the transaction always occurs either at the ask or bid in that mechanism, the actual series of transaction prices is a sequence of conditional expectations and therefore a martingale (Hasbrouck 2007, p.48). In other words, this adverse-selection effect does not appear as the serial covariance of actual transaction returns. According to our graphical data analysis in Section 4.2, (iv) is not

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<sup>5</sup>We apply the approximation  $\ln(1 \pm s/2) \approx \pm s/2$  for simplifying the expressions and making the numbers comparable with those from Corwin-Schultz measure under the assumption that the spread may be small. Those figures suggest that the spread may actually be large so our approximation strategy may not be accurate.

compelling as a major component of the observed serial covariance of transaction returns.

(i) is associated with the order processing, commission fees and deposits specific to the JEPX membership, as explained in Section 2.2. The PPSs have to pay some fees for using electricity transmission system owned by the regional monopolists. It is an additional contribution to the marginal cost of trades in the JEPX. Moreover, because the system price in the JEPX is determined as the intersection of aggregated market demand and supply schedules, there are multiple players involved in the demand side and supply side for a specified amount of electricity to be traded in total. If the breakdown of a power generator makes non-fulfillment of the agreed quantities to be supplied, the compensation scheme involves multiple players and therefore the transaction cost in that case becomes large. The multiple participants also increase the possibility of “hanuke yakujou” (intermittent bids): suppose a steel maker wants to sell electricity generated by the steam power in the process of cooling the heated steel during its operation of a factory from 9AM to 5PM. However, the suppliers and demanders are assigned with some randomness. The steel company can only sell electricity at 10:30-11 and 15-15:30 with a long duration in between. The intermittent generation and supply of electricity as such may not be efficient.

Regarding (ii), as is noted in Section 2.3, we can re-interpret the classical inventory model by Garman (1976) as a model for suppliers of immediacy in the face of large order imbalances. This is more pertinent to the JEPX market because, firstly, the market has no dealers, and secondly, the commodity for trade is non-storable electricity so that immediacy of trade agreement is crucial for avoiding the loss of supply and demand. A hockey-stick-shaped supply curve of Kanamura and Ohashi (2007) implicitly relies on a similar argument with a higher marginal cost associated with a larger quantity to be supplied. Jagadeesh and Titman (1995) show that the price reversal and its different degree over different sampling frequencies are consistent with the inventory model. However, this story does not mean that the traded amount of electricity explains the size of estimated spreads. Although the time-series averages of estimated spreads in Figure 10 resemble the time-series average of quantities in Figure 2, the latter has no explanatory power for the former once we control the time-of-a-day fixed effects and the market-wise time effect<sup>6</sup>. Recall that the inventory model predicts that the immediacy suppliers desire to keep their inventory at some preferred level, and it may not be parallel to the amount of trade in the market (Hasbrouck 2007, p.109).

Overall, the estimated spreads suggest that the efficiency of the JEPX is far from sufficiency. The reduction of high trading cost should be the first priority to improve the trading environment and attract potential power producers and suppliers. The complicated procedure associated with the case of non-fulfillment of the agreed delivery and the large order imbalances

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<sup>6</sup>This is confirmed by the following panel-data regression for estimated  $m$ -th monthly spread in  $j$ -th half-hour interval,  $s_{j,m}$ , as the regressand onto the quantities traded  $q_{j,m}$  with the same index convention:

$$s_{j,m}/2 = \alpha + \beta q_{j,m} + c_j + \tau_m + \epsilon_{j,m}, \quad (6)$$

where  $c_j$  is the  $j$ -th commodity-specific fixed effect and  $\tau_m$  is the market-wise time effect. The panel regression result is summarized as follows (the cluster-robust standard errors are in the parenthesis):

$$s_{j,m}/2 = \underset{(.540)}{6.517} - \underset{(0.0014)}{0.0013} q_{j,m}, \quad R^2 = .580$$

Therefore, the traded quantities have no power to explain the spreads.

are clear candidates to deal with, as are predicted by the two relevant microstructure models. The periodic call auction mechanism is often reported to be superior to the continuous auction or to the dealership in a usual financial market with many participants are involved (Amihud and Mendelson 1991). However, the non-storable nature of electricity and the multiple yet fewer participants in the JEPX market may cast some doubt on such theoretical prediction directly imported from a well-functioning financial market. As a tentative compromise, the introduction of dealers or market makers may be better than the current mechanism. However, the dealership market has its own drawbacks, so the design of trading system should be carefully conducted with solid numerical and empirical evidences. We hope that our paper triggers all these types of discussion for the improvement of the JEPX system.

## 5 Conclusion

We empirically document the first order serial covariance of transaction returns in the Japanese Electric Power Exchange (JEPX) over 48 half-hour intra-daily intervals in daily and weekly frequencies. Theoretical models in the field of market microstructure suggests that the order-processing cost and the inventory cost of immediacy suppliers are good candidates for explaining the existence of such serial covariance of transaction returns. Given preliminary data analysis and a permanent-transitory model of the transaction log prices as the sum of efficient counterpart and the market microstructure component, we measure the implied half-spread cost by three different methods. The resulting measures tend to be at least 50 times as large as the one based on the daily closing prices of the S&P500 index futures, implying a huge cost of transaction and inventory in the JEPX.

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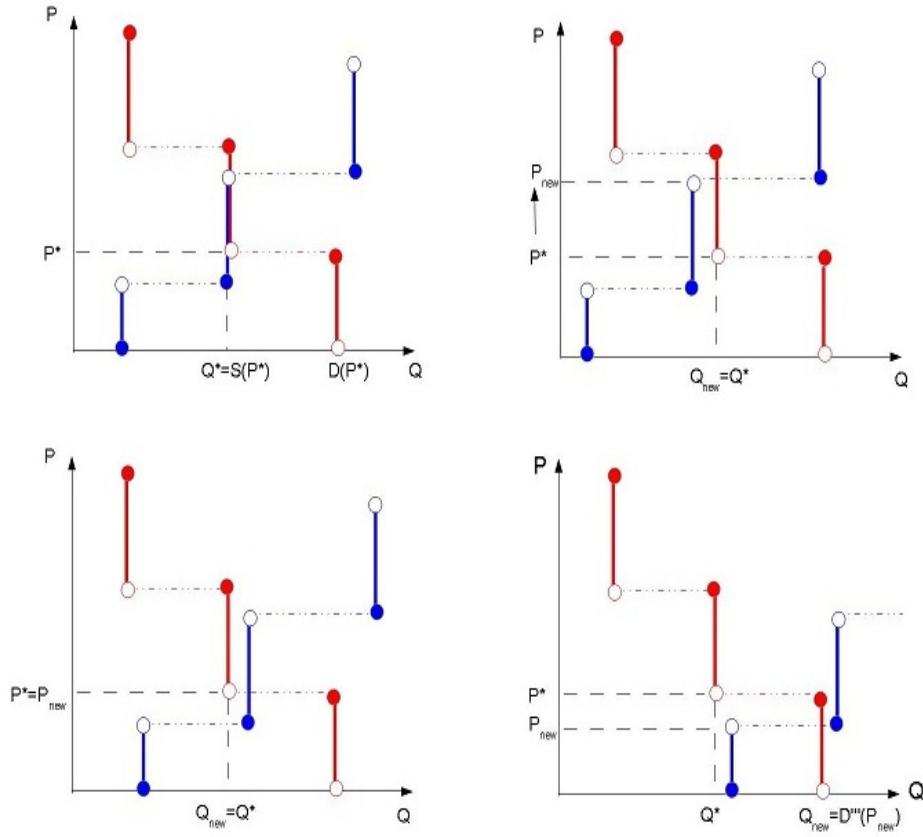


Figure 1: Discrete Demand and Supply Schedules. The equilibrium price condition is given by  $P^* = \inf\{P \geq 0 : S(P) \geq D(P)\}$ . At  $P = P^*$ ,  $S(P^*) < D(P^*)$  so that this  $P^*$  cannot be attained by the minimum of such  $P$ . Although some investors quote the demand  $D(P^*)$  for such price, it is not executed according to the JEPX limit order rule.

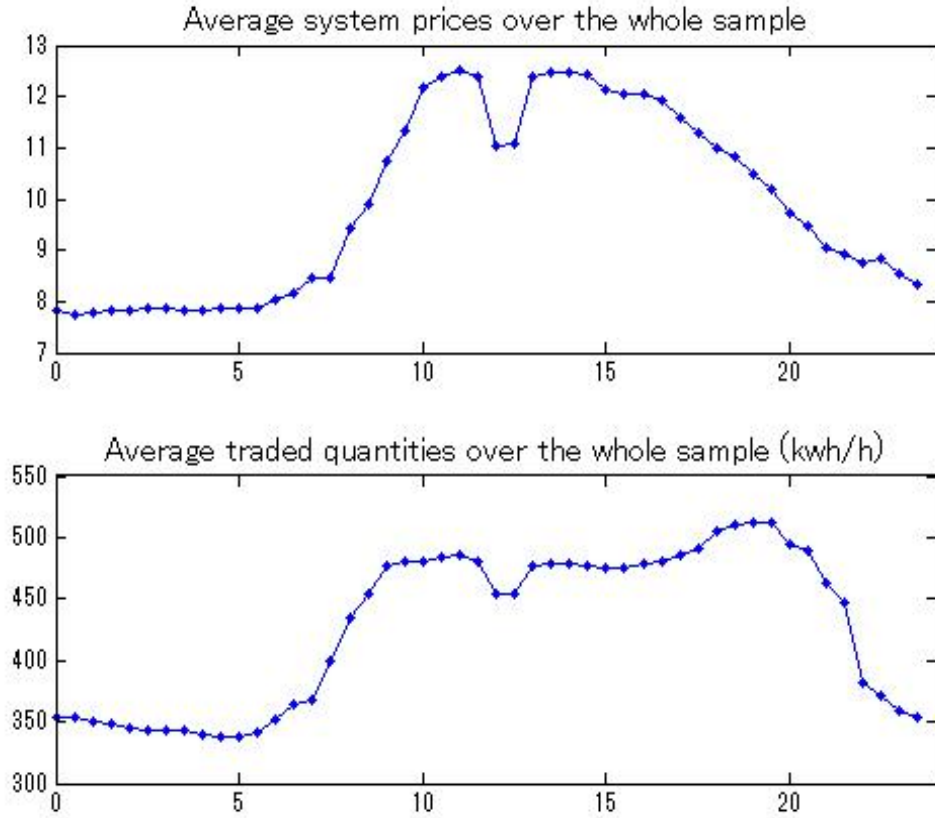


Figure 2: Time-Series Averages of System Prices and Traded Quantities for 48 half-hour intervals over the entire sample. The sharp trough in the middle of the day corresponds to 12-13 for the lunch-time break. 0-0:30 and 11:30-12 are representative periods recording the lowest/highest system prices on average. The traded quantities identify the daytime period from 8 to 22, and the nighttime period from 22:30 to 7:30 in the next morning.

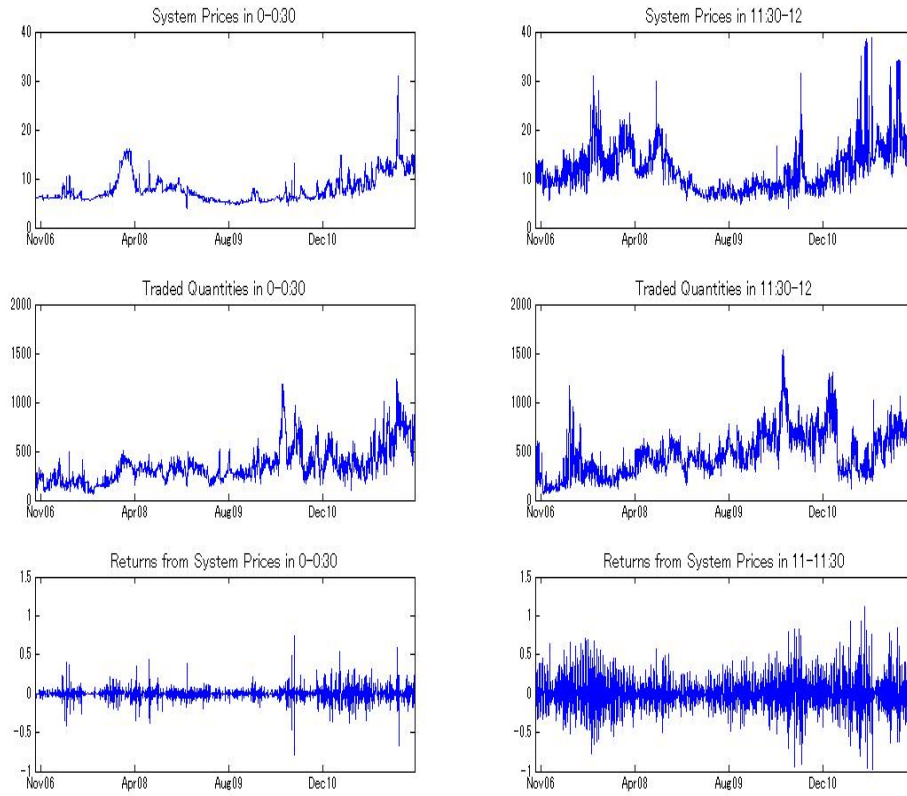


Figure 3: Time Series Plots of System Prices, Traded Quantities and Returns for 0-0:30 (the left column) and 11:30-12 (the right column). Depending on the time of a day, the fluctuation of prices and traded quantities differ substantially.

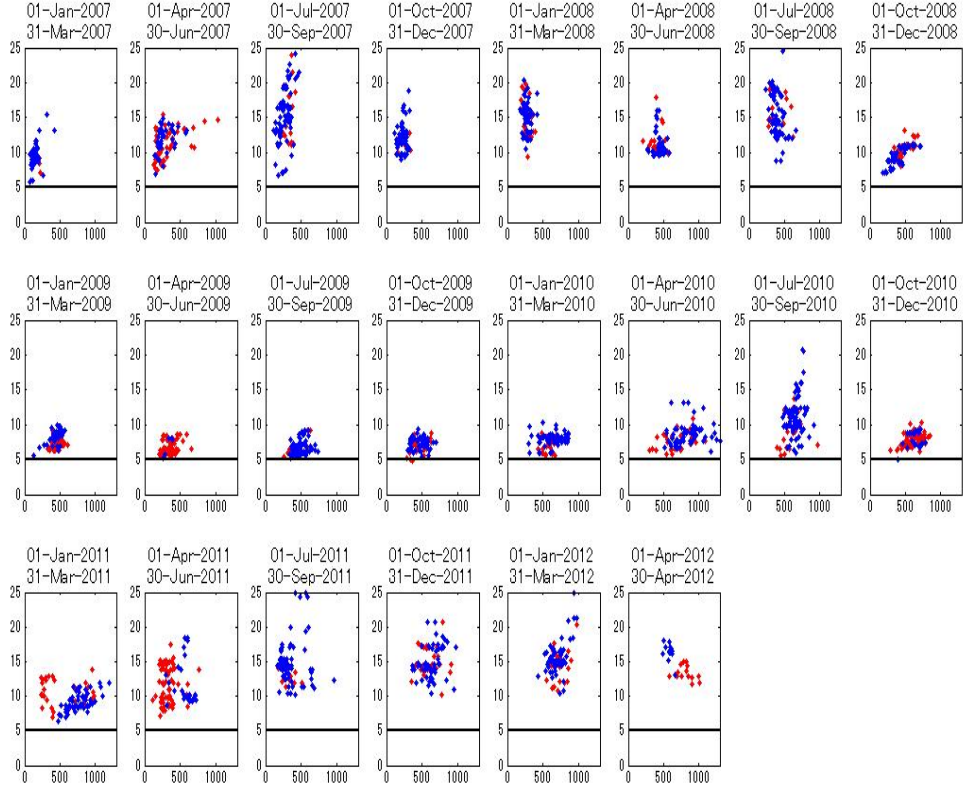


Figure 4: Scatterplots of System Prices against Traded Quantities for each quarter. Given the time-lag of installment and augmentation of the power generation system, the plots for each quarter can be interpreted as traces of a supply curve in each period caused by the random fluctuation of the relatively inelastic demand schedule. Almost all trades occur at prices above 5 yen (per kwh/h). It is consistent with the all-time backup system. The red dots are the pairs of traded quantities and system prices calculated as the average of prices at Tokyo and Kansai area when the east-west linkage of electricity delivery breaks down due to, e.g., the excess capacity.

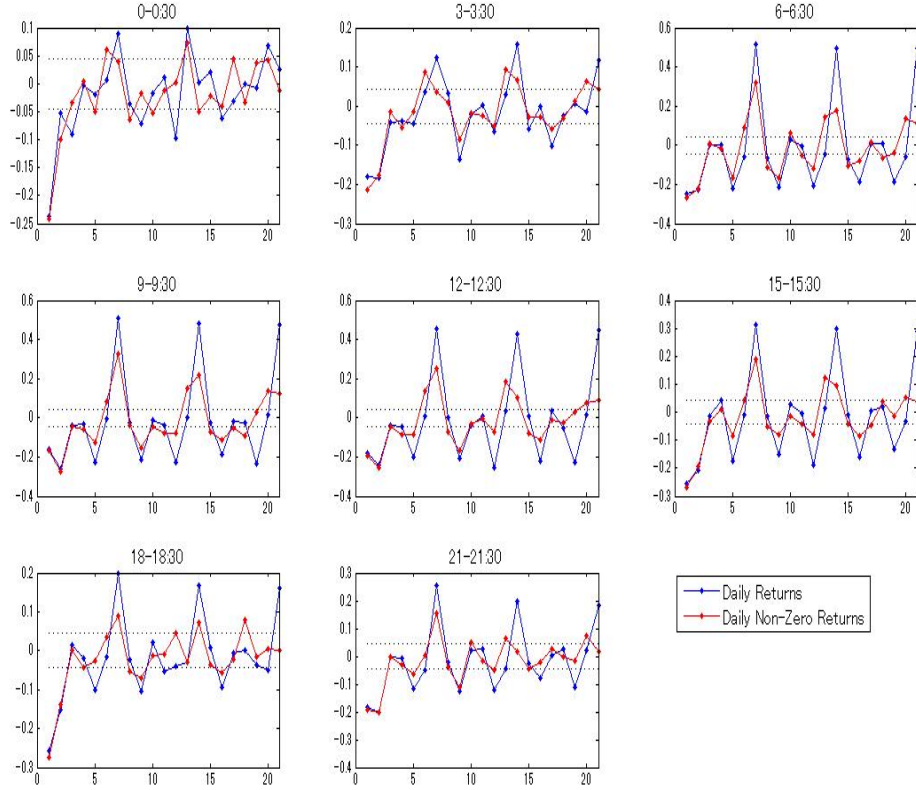


Figure 5: Autocorrelation functions of daily returns for 8 different intra-daily half-hour intervals. The two parallel breaking lines are 95% confidence intervals given the white-noise null. The blue ones are for daily raw returns while the red ones are for daily non-zero returns. The degree of serial correlation seems milder for the non-zero returns than for the raw returns. In all half-hour intervals, the first order autocorrelation is significantly negative. Reflecting the day-of-a-week effect, the autocorrelation functions show a clear 7-day cycle.

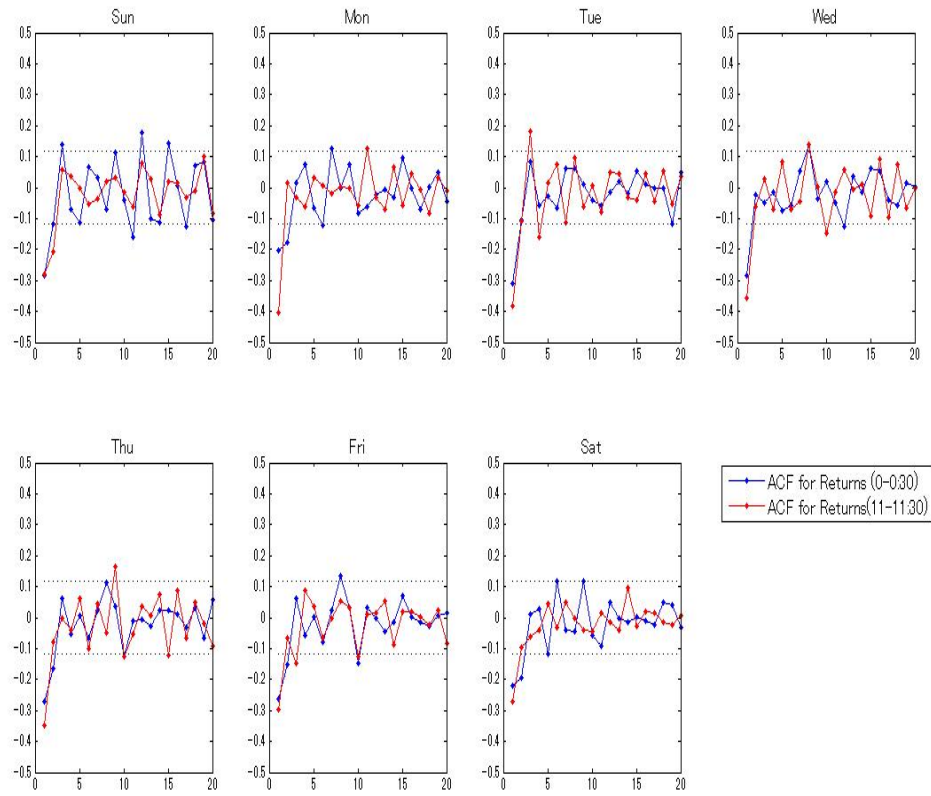


Figure 6: Autocorrelation functions for weekly returns. The different magnitudes of the first-order negative autocorrelation is visible for different days of the week are visible, especially for the interval from 11:30 to 12.

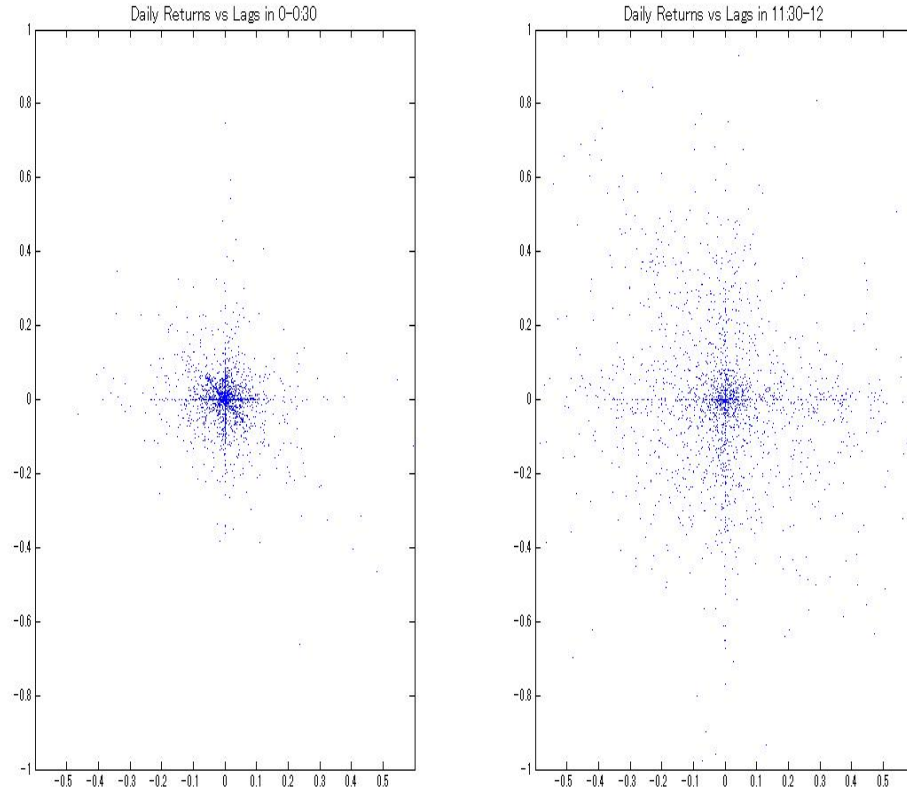


Figure 7: Daily Returns against their own immediate lags. The left panel for the returns in the midnight electricity suggest the presence of rays from the origin to the direction of horizontal and vertical axis, and from the north-west to south-east direction. They are mainly caused by the zero returns and the first order serial correlation. The right panel is for the returns from 11:30 to 12. The ray from the north-west to south-east direction is blurred. Overall, the price discreteness may not be so crucial.



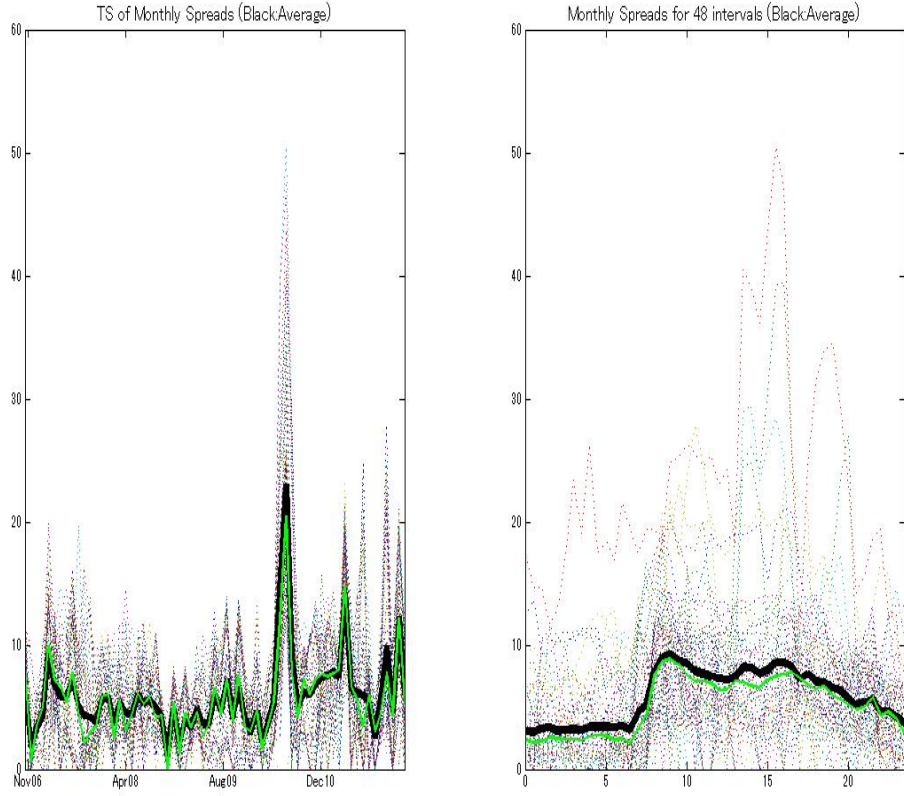


Figure 8: Monthly spread estimates in percentages of the efficient prices based on the bias-corrected version of Roll's measure. The left panel stores the time-series of estimated spreads for the returns in the midnight electricity suggest Trajectories in bold black and green are the cross-sectional mean and median of spreads for 48 different commodities, respectively. They show two clear spikes associated with the record-breaking hot summer in 2010 and the aftermath of 11-March-2011 earthquake. The right panel records the intra-daily spreads of 48 commodities (each trajectory corresponds to the 48 spreads in each month). The bold black and green curves are the time-series mean and median of estimated spreads over the whole number of months.

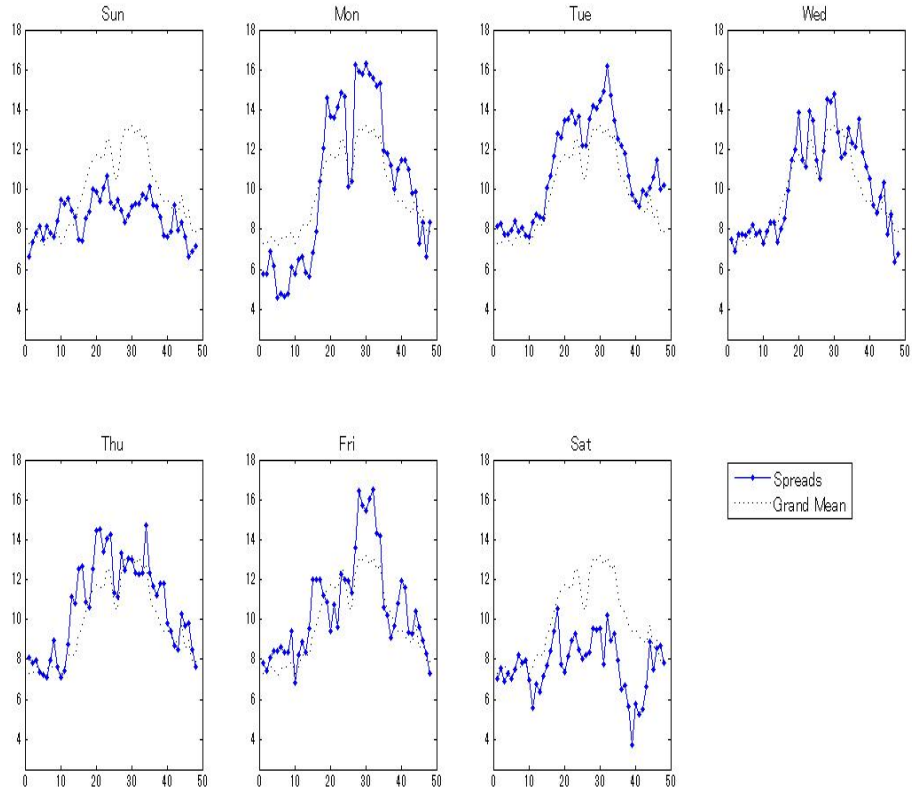


Figure 9: Spreads based on weekly returns, estimated using entire sample period. The breaking trajectory is the average of all weely spreads from all days of the week. The figures show that monday, tuesday and friday contribute to the level of average weekly spreads while spreads for Saturday and Sunday show relatively flat patterns over the whole time of a day.

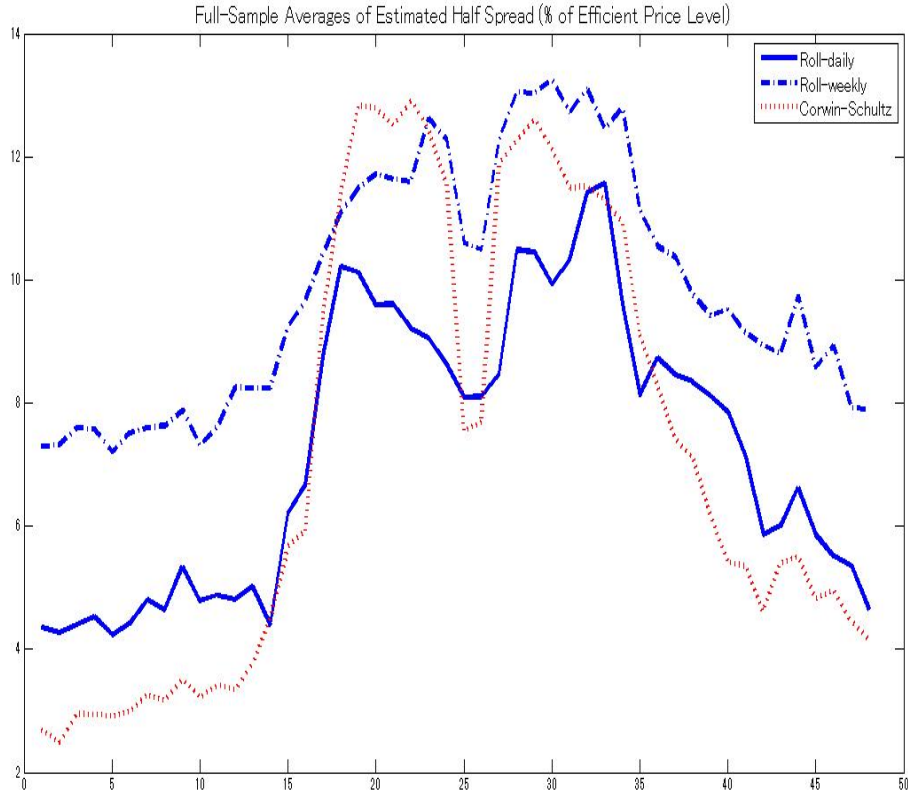


Figure 10: Alternative spread measures in percentages of the efficient prices. The real and breaking lines in blue are the full-sample average of monthly spreads from the bias-corrected Roll method based on daily returns and weekly returns, respectively. The red dotted line is the full-sample average of monthly spreads estimated by the Corwin-Shultz method as the within-month average of estimates in the 20-day rolling-window. For the daytime period with active trades of electricity, the Corwin-Shultz estimates are roughly in the middle of two versions of Roll measures based on daily returns and weekly returns while they are below them in the night-time period, as is consistent with the fact that the accuracy of a range-based estimator requires great variation of data during the period for defining it. It seems that the true spreads should lie on average between two blue lines.